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Low Cost Inertial Sensors for the Motion Tracking and Orientation Estimation of Human Upper Limbs in Neurological Rehabilitation

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ABSTRACT This paper presents the feasibility of utilizing low cost inertial sensors such as those found in Sony Move, Nintendo Wii (Wii Remote with Wii MotionPlus) and smartphones for upper limb motion monitoring in neurorehabilitation. Kalman and complementary filters based on data fusion are used to estimate sensor 3D orientation. Furthermore, a two-segment kinematic model was developed to estimate limb segment position tracking. Performance has been compared with a high-accuracy measurement system using the Xsens MTx. The experimental results show that Sony Move, Wii and smartphones can be used for measuring upper limb orientation, while Sony Move and smartphones can also be used for specific applications of upper limb segment joint orientation and position tracking during neurorehabilitation. Sony Move's accuracy is within 1.5° for Roll and Pitch and 2.5° for Yaw and position tracking to within 0.5 cm over a 10 cm movement. This accuracy in measurement is thought to be adequate for upper limb orientation and position tracking. Low cost inertial sensors can be used for the accurate assessment/measurement of upper limb movement of patients with neurological disorders and also makes it a low cost replacement for upper limb motion measurements. The low cost inertial sensing systems were shown to be able to accurately measure upper limb joint orientation and position during neurorehabilitation.

INDEX TERMS Inertial tracking, kinematic model, low cost inertial sensors, upper limb motion, 3D motion tracking.

I. INTRODUCTION

Human motion analysis is commonly used for diagnosis and monitoring the efficacy of treatment in rehabilitation of the lower and upper limbs. Camera based systems are still the gold standard for motion tracking within the laboratory and clinic [1]. However, the required measurement space, the cost of equipment and the complexity of set up limits the use of the camera tracking system to specialized clinics and laboratories. Because of these restrictions, alternative technologies using magnetic and mechanical sensing [1] have been developed. Of special interest has been the development of Micro-Electro Mechanical Systems (MEMS) which has resulted in high quality miniature inertial sensing units whose size and weight are suitable for attachment to the human body [2], [3]. One example of a commercial inertial sensor is the Xsens MTx [4] which incorporates a tri-axial accelerometer, rate gyro and magnetometer to enable sensor orientation tracking and, when combined with a kinematic model, limb segment position tracking.

What makes the use of inertial sensors particularly attractive is that motion tracking measurements can be performed outside the environment of a specialized clinic or lab, and without the need to be within the restricted field of view of a camera system. Additionally, inertial measurements may provide more direct data on limb segment joint acceleration and angular velocity in a local rather than a specialized setting [5]. Commercial inertial sensing systems designed for biomechanical applications are relatively expensive (£4000 for a two-sensor system) which limits their potential use in more

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general clinical applications where cost is a significant factor in controlling the uptake of new measurement techniques. However, mass produced and hence lower cost inertial sensors are now widely used in gaming controllers. Common examples are the Nintendo Wii [6] and the Sony PlayStation Move [7]. Therefore there is considerable value in exploring the feasibility of repurposing such devices as low-cost alternative solutions for medical use e.g. rehabilitation [8]. For most of these devices programming interfaces are now available to acquire the sensor data through a PC. Gaming systems such as the Nintendo Wii and Microsoft Kinect have already been used in virtual reality and camera-based tracking research [9]. More specifically, the Kinect devices had been used together with Inertial Measurement Unit (IMU) to provide reliable upper limb motion monitoring, where the Kinect devices are generally used as references for absolute position. Kalkbrenner *et al.* [10] propose a system to track limb movements by fusing the optical information from Kinect and data from IMU, of which Kinect was used for absolute positioning to compensate the drift from the IMU. Glonek and Wojciechowski [11] fuse the Kinect depth sensor and the IMU data to compensate for the limitations of both measurement devices. However, the use of the camera raises the concern on the privacy issues and may cause the patients unpleasant or uncomfortable during assessment. In consideration of the patient's privacy and object of reducing system complexity, in this paper we focus on assessing the upper limb motion solely based on an IMU system. It has been show that it is possible to utilize IMU sensors (e.g. Xsens MTx with integrated Kalman filters) for upper limb motion tracking without referencing an optical system [5], [12]. The use of IMU for the estimation of limb segment orientation and position has led to the development of data fusion methods. Madgwick *et al.* [13] have implemented an algorithm to estimate IMU orientation using a gradient descent method. More recently, Lee and Choi [14] focused on the development of a constraint-augmented Kalman filter (KF) which dealt with an acceleration-level kinematic constraint. In this work, in order to estimate the orientation by the low cost gaming sensor, a complementary filter and a Kalman filter has been developed and evaluated. Though more recently, smart watches and fitness trackers have emerged as wrist wearable inertial sensing units that can capture limb motion data [15], [16]. This technology, when incorporating access to the IMU data, may prove to be an attractive replacement for the larger gaming sensors and smartphones as they are small and designed to be attached to the upper limbs.

Low cost solutions for assessment of upper limb movement of patients undergoing neurorehabilitation are very limited. In this paper we explore the feasibility of using low cost inertial sensors embedded in gaming controllers and smartphones, for monitoring upper limb motion during rehabilitation. Experiments were conducted in a typical Neurorehabilitation Unit of a UK Hospital. Preliminary results on the performance of the Nintendo Wii MotionPlus - six degrees of freedom (6DOF) - Sony Move (9DOF) and a smartphone (9DOF) are presented. The proposed low cost inertial sensing system in this work is a proof of concept which utilizes low cost Sony Move gaming controllers which are not originally developed for biomechanical applications. We also propose the calibration procedures and sensor fusion algorithms and kinematic modelling for using the low cost inertial sensors in rehabilitation scenarios and the proof of concept system has been evaluated on both the healthy volunteers and patients. Further analysis is focused on the use of the Sony Move device, where a system is developed and evaluated for a low cost upper limb motion tracking system. Results are compared to a commercial highly-accurate inertial sensing unit Xsens MTx [5], [17]. The outcome of this study indicates that a low cost 9DOF IMU systems using sensors such as the Sony Move can be used for selected upper limb position tracking assessments during neurorehabilitation. The proposed low cost system has shown the potential to benefit both the clinicians and doctors in clinical settings and also makes the home rehabilitation assessment for patients a viable option and reduces the outpatients' hospital visits.

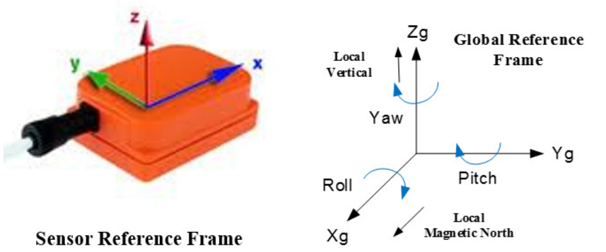
II. CHALLENGES

Upper limb neurological rehabilitation typically involves regular assessment of upper limb mobility. Such assessment involves a range of upper limb range of motion and fine motor skill tasks that need to be monitored and recorded accurately. Accurate capture of the upper limb movement can allow the regular monitoring of the patients' condition. Our main objective is to IMUs to capture an accurate 3D representation of the patients' upper limb movement during such exercises.

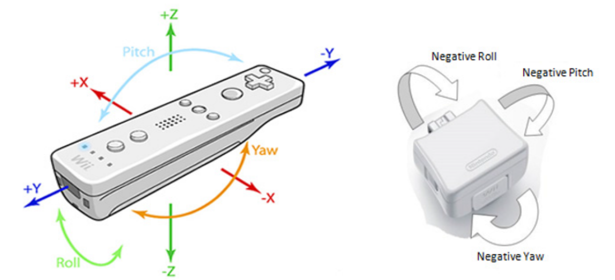
In order to obtain upper limb segment movement data from IMUs output it is necessary to have calibrated sensors and to apply a kinematic model to the output of those sensors. Inertial sensors embedded in low cost game controllers are typically not calibrated, nor is a kinematic model provided. Therefore, static and dynamic calibration of the sensors and the development of a kinematic model is required.

Tracking the movement of the calibrated sensor requires an accurate estimation of the sensors' orientation. To do this, sensor inclination (roll and pitch) and heading (yaw) information need to be estimated. Inclination can be estimated from the accelerometer output as long as there is no translational movement. However, the accelerometer can only measure sensor orientation relative to the gravitational field, but not heading around the vertical axis (See Fig. 1 (a)). Heading (Yaw) can be estimated by fusing the outputs from both magnetometer and accelerometer, but a more accurate estimate of sensor orientation can be obtained by integrating the rate gyro output and fusing this data with that from the accelerometer and magnetometer using a Kalman filter [3], [18].

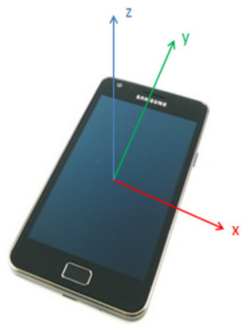
Once the estimate of sensor orientation has been optimized then this information can be applied to a kinematic model to estimate 3D limb segment position. However, the use of a kinematic model to track the relative position between two limb segments – e.g. upper and lower arm segments - requires the use of an IMU with 9DOF. This means that only those



(a) Xsens MTx inertial sensor reference frame coordinates



(b) Wii Remote and Wii MotionPlus's local reference frame coordinates



(c) The Sony Move and local reference frame coordinates
(d) The Smartphone and local reference frame coordinates

FIGURE 1. **Inertial sensing units used in this study.**

sensors which contain a 3D accelerometer, magnetometer and rate gyro can be used. Therefore sensors such as the Nintendo Wii motion, which only contains a 3D accelerometer and rate gyro, can only be used for basic measurements such as orientation of a single segment and movement of that segment in space, but not movement relative to limb joints or other segments.

III. SYSTEM SETUP AND METHODOLOGY

In the following sections four different IMU systems will be presented. The Xsens MTx, Nintendo Wii (Wiimote), Sony Move and Samsung Galaxy SII Smartphone (See Fig. 1).

A. SENSORS

1) HIGH ACCURACY COMMERCIAL INERTIAL SENSOR - Xsens MTx

The Xsens MTx sensor in Fig. 1 (a) is used as the standard / reference inertial measurement unit for upper limb motion tracking. The MTx is 38×53 × 20.9 (L×W×H) mm and weighs 30g. The MTx can provide calibrated 3D acceleration, rate gyro, and magnetic field data. This data is used to estimate sensor orientation in the sensor reference frame and the global reference frame. The orientation of the MTx relative to the global reference frame is estimated using the inbuilt extended Kalman filter which fuses the accelerometer, gyroscope and magnetometer data. According to the device specifications the MTx has an angular resolution of 0.05° and static accuracy of 0.5°.

2) LOW COST INERTIAL SENSORS

Since the low cost inertial sensors presented in this work are either gaming controllers or smartphones, there is limited information about the IMU type and specifications.

a: WII MOTION CONTROLLER

Nintendo released the Remote in 2006 (Fig. 1 (b)) which incorporated a tri-axial accelerometer (ADXL330), with a range of ±3g [19]. The Wii Remote's dimensions are 148 × 36×31 (W×L×H) mm. Compared to the MTx, the Wii Remote is significantly larger which makes it difficult to attach to a limb segment. Because the Wii Remote does not incorporate a gyro and magnetometer, only rotation around the x-axis and y-axis (roll and pitch angle) can be estimated (based on changes with respect to gravity). In order to improve the response of the Wii Remote, Nintendo released the Wii MotionPlus attachment in 2009 (Fig. 1 (b)). This attachment incorporates two InvenSense IDG-600 bi-axial gyros to produce a 3-axis gyroscope. The range of gyroscope IDG-600 is ±500 to 2000°/s, and its sensitivity is 0.5 mv/°/s [19]. This operating range is well within those expected in normal human movement as they are designed for active gaming. This attachment enables the controller to track the rate of change in roll, pitch and yaw. However, these values represent relative movement. In order to estimate the absolute roll, pitch and yaw in the global reference frame, the initial yaw should be known. The initial yaw can be estimated through a magnetometer, which is not available in the Nintendo Wii. Therefore, the Nintendo Wii is restricted to 2D movement estimation on a vertical plane with respect to ground. A further limitation of the Wii, as with all the low cost sensors, is that the outputs are not calibrated.

The remote has, however, the advantage of incorporating a Bluetooth transmitter, which removes the need for connecting cables. In this evaluation, data from the Wii were captured using the Bluesoleil8.0 [20] Bluetooth stack. The Brian Peek's API, a managed library for .NET is available for Wiimote [21] which enables raw data to be retrieved from the Wiimote controllers by accessing the Windows HID interface. WiimoteLib1.8 is used to acquire data from multiple Wiimotes and, fWIInev0.4matlab [22], is used to apply the kinematic model in Matlab. Currently the maximum sample rate rate for a single Wiimote is 100Hz and for two Wiimotes, 50Hz, which is adequate for human motion analysis.

b: SONY MOVE CONTROLLER

Sony released the Playstation Move in 2010 [7]. The Sony Move's dimensions are 200 × 47 × 47 mm which is similar to the Wii. Unlike the Wii, the Sony Move (Fig. 1 (c)) has the required 3D accelerometer, gyroscope and magnetometer for the estimation of 3D orientation. This indicates that the Sony Move can be a potential low cost replacement for the MTx in those applications where physical dimensions are not a critical factor. The triaxial accelerometer is a Kionix KXSC4 102272410 [23] which has a sensitivity of about 0.250V/g with an operating range of ±6g. The 3D gyroscope unit comprises one 2-axis gyroscope (x, y) and one 1-axis gyroscope (z). The magnetometer is a 3-axis AKM AK8974 magnetic compass. As with the Nintendo Wii, calibration will be required (Section IV.A). The Ultra Mini Bluetooth 2.1+EDR Bluetooth Dongle along with the MotioninJoy driver [24] were used for the Bluetooth connection between the Move and PC. Sensor data from the Move was collected through the PSMoveLib [23] (developed as part of the project MoveOnPC). This software controls communication between the Sony Move and the PC and can control several Sony Move devices. The PSMoveLib allows the acquisition of real-time acceleration, rate gyro, and magnetic field data. A sampling rate of 60 updates per second is possible for a single controller. The relationship between the number of Move devices (N), and sample rate per device is 60/N Hz. Therefore the sample rate will drop to 30Hz if two Sony Move controllers are connected. It should be noted that the minimum number of controllers that can be used to track upper limb motion is two and that a sample rate of 30Hz is adequate for monitoring this movement. Once the sensor has been calibrated then this data can be fed into the kinematic model.

c: ANDROID PHONE - SAMSUNG GALAXY SII

Recent developments in integrating a tri-axial accelerometer, magnetometer and gyroscope into smartphones gives them similar functionality to the XSens MTx sensor. Though their cost is higher than gaming controllers, their popularity means that they are readily available and single sensor applications are now being evaluated. In this paper a preliminary evaluation of the Samsung Galaxy SII android phone (Fig. 1 (d)) is presented. This phone incorporates a K3DH accelerometer, a K3G gyroscope sensor, and an AK8975 magnetic field sensor. Data is acquired using the Android SDK and then saved onto the internal SD card. This data can be transferred to a PC via Wi-Fi or Bluetooth for data post-processing.

B. 3D ORIENTATION ESTIMATION AND POSITIONTRACKING

1) 3D ORIENTATION ESTIMATION

An essential part for tracking limb segments using a kinematic model is to estimate the relative position of two or more sensors attached to the different limb segments with respect to a reference point (e.g. body trunk). To do this the orientation of each sensor in a common reference frame must be estimated. This common reference frame is often called the global reference frame, whose axes are defined relative to magnetic north and the vertical gravitational field. Data from the magnetometer and the accelerometer is used to define the relationship between the sensor reference frame and the global reference frame. The orientation of the MTx sensor in the local and global reference frame is calculated within the MTx using an embedded algorithm utilizing the Xsens implementation of a Kalman filter. This data can then be used in a kinematic model to estimate changes in limb joint orientation and limb segment position. However, the low cost inertial sensors under consideration only provide raw, uncalibrated outputs from the accelerometer, gyroscope and magnetometer. Therefore once the sensors have been calibrated (Section IV.A), 3D orientation and hence sensor rotation can be estimated by fusing the accelerometer, gyroscope and magnetometer data using either a Complementary filter [18] or a Kalman filter [3]. Roll (φ), Pitch (θ) and Yaw (ψ) define the sensor rotations around the x, y, z axes in the global reference frame, of which x points to magnetic north, y to local west and z to local vertical (see Fig. 1 (a)). The details of Roll and Pitch estimation from acceleration can be found in our previous work [5]. Combining the accelerometer data with data from the magnetometer, the heading (Yaw, ψ) [25] when the sensor is at rest can be estimated, as shown below (1)(2)(3):

$$\varphi = tan^{-1}\left(\frac{acc_y}{\sqrt{acc_x 2 + acc_z{}^2}}\right) \tag{1}$$

$$\theta = tan^{-1}\left(\frac{acc_x}{\sqrt{acc_y{}^2 + acc_z{}^2}}\right) \tag{2}$$

$$\psi : \begin{cases} X_h = mag_x * cos(\theta) + mag_y * sin(\theta) * sin(\varphi) \\ \qquad +mag_z * sin(\theta) * cos(\varphi) \\ Y_h = -mag_y * cos(\varphi) + mag_z * sin(\varphi) \\ \psi = tan^{-1}(\frac{Y_h}{X_h}) \end{cases} \tag{3}$$

where, mag_x, mag_y and mag_z are the magnetometer outputs from the inertial sensor x, y and z axes, respectively. acc_x, acc_y and acc_z are the acceleration outputs from the inertial sensor.

Though the accelerometer and magnetometer data can be fused to provide Roll, Pitch, and Yaw, orientation tracking estimation using these two sensors is susceptible to noise and cannot provide orientation tracking of sufficient accuracy, especially when there is translational movement [26]. However it has been shown that the gyroscope rate of turn data, $\omega = [\omega_x, \omega_y, \omega_z]^T$, can help provide a more accurate estimate of changes in sensor orientation in time δt, by applying the Rotation matrix, R(δt) of equations (4) (5) [26].

$$R(\delta t) = \begin{bmatrix} 1 & -\omega_z * \delta t & \omega_y * \delta t \\ \omega_z * \delta t & 1 & -\omega_x * \delta t \\ -\omega_y * \delta t & \omega_x * \delta t & 1 \end{bmatrix} \tag{4}$$

$$R(t + \delta t) = R(\delta t) * R(t) \tag{5}$$

where R(t+δt) is the orientation at time (t+δt).

The rotation matrix can be solved by using the Euler angle represented by (6):

$$
\begin{aligned}
R_{GS} &= R_z(\psi) * R_y(\theta) * R_x(\varphi) \\
&= \begin{bmatrix} cos\psi & -sin\psi & 0 \\ sin\psi & cos\psi & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} cos\theta & 0 & sin\theta \\ 0 & 1 & 0 \\ -sin\theta & 0 & cos\theta \end{bmatrix} \\
&\quad \times \begin{bmatrix} 1 & 0 & 0 \\ 0 & cos\varphi & -sin\varphi \\ 0 & sin\varphi & cos\varphi \end{bmatrix} \\
&= \begin{bmatrix} R_{11} & R_{12} & R_{13} \\ R_{21} & R_{22} & R_{23} \\ R_{31} & R_{32} & R_{33} \end{bmatrix}
\end{aligned} \tag{6}
$$

The Euler angles can be obtained from the Rotation matrix by (7):

$$
\begin{cases}
Roll : \varphi = tan^{-1}\left(\dfrac{R_{32}}{R_{33}}\right) \\
Pitch : \theta = -sin^{-1}(R_{31}) \\
Yaw : \psi = tan^{-1}\left(\dfrac{R_{21}}{R_{11}}\right)
\end{cases} \tag{7}
$$

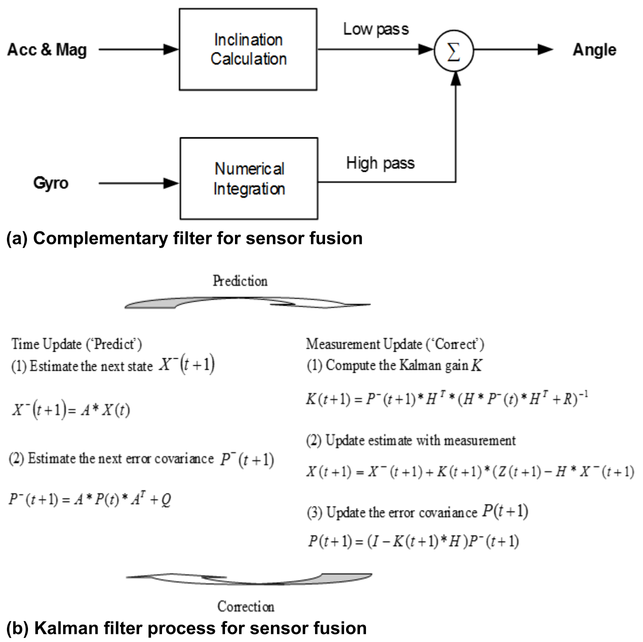
If the initial orientation is known it is theoretically possible to use the gyro data alone to estimate sensor orientation over time. But as is the case for the accelerometers and magnetometers, the gyros also have offsets and gains which change over time and with temperature. These offsets and drifts introduce errors in the estimate of sensor orientation and then errors of the order of meters in estimating sensor position after a couple of seconds. Therefore, to minimize these errors in sensor orientation, the data from the three sensors is fused. The application of two standard techniques for minimizing these errors, the Complementary filter, and the Kalman filter, are described in the following sections.

a: COMPLEMENTARY FILTER

It has been found that both the accelerometer and magnetometer data provides a good measure of static and low frequency changes in orientation while gyroscope data is a good indicator of higher frequency changes in orientation. Therefore the complementary filter is designed to combine or fuse the low-pass filtered accelerometer and magnetometer signal and the high-pass filtered gyroscope signal to reduce the effect of offsets and drifts in the sensor signals [27]. This filter is described in equation (8) and Fig. 2 (a).

$$
\begin{bmatrix} Roll \\ Pitch \\ Yaw \end{bmatrix}_t = (1-\alpha) * (R(\delta t) * R(t-1)) + \alpha * \begin{bmatrix} Roll_{acc\&mag} \\ Pitch_{acc\&mag} \\ Yaw_{acc\&mag} \end{bmatrix}_t \tag{8}
$$

where $R(t-1)|_{t=1} = \begin{bmatrix} Roll_{acc\&mag} \\ Pitch_{acc\&mag} \\ Yaw_{acc\&mag} \end{bmatrix}_0$ is the initial condition. $(R(\delta t) \cdot R(t-1))$ is the orientation estimation from the gyro output. $\begin{bmatrix} Roll_{acc\&mag} \\ Pitch_{acc\&mag} \\ Yaw_{acc\&mag} \end{bmatrix}$, calculated from (1) (2) (3), provides the orientation estimation from the accelerometer and magnetometer outputs. The filter coefficient, α is adjusted to optimize the high and low pass filter characteristics. The evaluation of this filter for the estimation of sensor orientation is presented in section IV.C.1.



(a) Complementary filter for sensor fusion

(b) Kalman filter process for sensor fusion

FIGURE 2. Methods for orientation estimation.

b: KALMAN FILTER

The Quaternion based Kalman filter, which is a development of the complementary filter, is another algorithm that can be used to fuse sensor data in order to reduce the effect of sensor offsets and drifts in the estimate of sensor orientation [28]. The basic principle of the Kalman filter is to estimate the sensor orientation by recursive operations and then to use the observed measurements to adjust the filter characteristics and to estimate future values of the orientation. It has been found that this technique results in an output which is less sensitive to noise and drift in the sensor data than the complementary filter [18]. The prediction and correction process for a Kalman filter is shown in Fig. 2 (b). This algorithm uses sensor fusion to estimate the rotation of the sensor by combining two estimates of orientation; one from the accelerometer and magnetometer and the other from the gyroscope.

In this study, state vector is X(t) = q(t) the quaternion, and the state matrix is $A = \Omega(\delta t)$. The state matrix is used to compute the state variable at the current time. Therefore, the process model uses the angular velocity measured by gyroscope to transform to quaternions rate:

$$\hat{q}(t)^- = \Omega(\delta t)\, q(t-1)$$

$$= \begin{bmatrix} 1 & -\omega_x & -\omega_y & -\omega_z \\ \omega_x & 1 & \omega_z & \omega_y \\ \omega_y & -\omega_z & 1 & \omega_x \\ \omega_z & \omega_y & -\omega_x & 1 \end{bmatrix} q\,(t-1) \tag{9}$$

The estimated process noise is related to the gyroscope noise. The state covariance is as follows in (10):

$$P(t)^{-} = \Omega\,(\delta t) * P(t-1) * (\Omega\,(\delta t))^{T} \tag{10}$$

In the predication stage, the state variables and their uncertainties are produced. The measurement value of orientation, the quaternion q(t) is then calculated using the acceleration and magnetometer estimation: $Z\,(t) = q_{acc\&mag}\,(t)$. The measurement model is given below:

$$\begin{aligned} &Z\,(t) \\ &= q_{acc\&mag}\,(t) \\ &= \begin{cases} q_0 = cos(\frac{\theta}{2})cos(\frac{\psi}{2})cos(\frac{\varphi}{2}) - sin(\frac{\theta}{2})sin(\frac{\psi}{2})sin(\frac{\varphi}{2}) \\ q_1 = sin(\frac{\theta}{2})sin(\frac{\psi}{2})cos(\frac{\varphi}{2}) + cos(\frac{\theta}{2})cos(\frac{\psi}{2})sin(\frac{\varphi}{2}) \\ q_2 = sin(\frac{\theta}{2})cos(\frac{\psi}{2})cos(\frac{\varphi}{2}) + cos(\frac{\theta}{2})sin(\frac{\psi}{2})sin(\frac{\varphi}{2}) \\ q_3 = cos(\frac{\theta}{2})sin(\frac{\psi}{2})cos(\frac{\varphi}{2}) - sin(\frac{\theta}{2})cos(\frac{\psi}{2})sin(\frac{\varphi}{2}) \end{cases} \end{aligned} \tag{11}$$

where φ, θ and ψ are, respectively, the Roll, Pitch and Yaw calculated from the acceleration and magnetometer output as (1) (2) (3). In the measurement update, the Kalman gain has been computed using (12).

$$K\,(t) = P^{-}(t) * (P^{-}(t) + R)^{-} \tag{12}$$

where R is the measurement noise covariance. The updates of the state vector and the covariance with the measurement are as the (13) and (14) below.

$$X\,(t) = X^{-}(t) + K(t) * (Z(t) - X^{-}(t)) \tag{13}$$

$$P\,(t) = (I - K(t))P^{-}(t) \tag{14}$$

When a new measurement is observed, the estimates of the state variables are updated based on a weighted average. The sensor orientation can now be used in a kinematic model of the limb to estimate limb segment joint orientation and position.

2) POSITION TRACKING BY KINEMATIC MODELLING

In order to estimate changes in body segment orientation and position, a kinematic model [29] is used. The complexity of this model depends on how many segments are to be monitored and what assumptions can be made. For example, a simple two-segment kinematic model can be developed to estimate upper limb joint orientation and position if the shoulder is assumed to be the fixed reference point and only movement relative to the shoulder is required. In this case only two sensors are required, attached to the upper and lower arm respectively. With this configuration the changes in the elbow joint angle and in the movement of the upper and lower arm can then be tracked relative to the shoulder - or trunk reference frame. If the shoulder cannot be kept stationary and measurement relative to another reference frame is required then three or more sensors and a three-segment model are required. Additionally, a sensor can be attached to the hand when hand movement is to be tracked. In this case a four-segment kinematic model is used. The kinematic model for this configuration and the performance of that system utilizing MTx sensors is described in our previous paper [5]. Unless the participant's trunk is stationary, additional sensors will be required on the participant's spine in order to monitor any spinal movement and a more complex kinematic model developed. Because of its physical size the feasibility of using a game controller like Sony Move for more complex monitoring will be limited by the need to attach more than two sensors to the participant. Therefore, for any practical purposes where such devices can be used for tracking upper limb movement, the most realistic scenario will involve two sensing devices attached to the two segments of the arm.

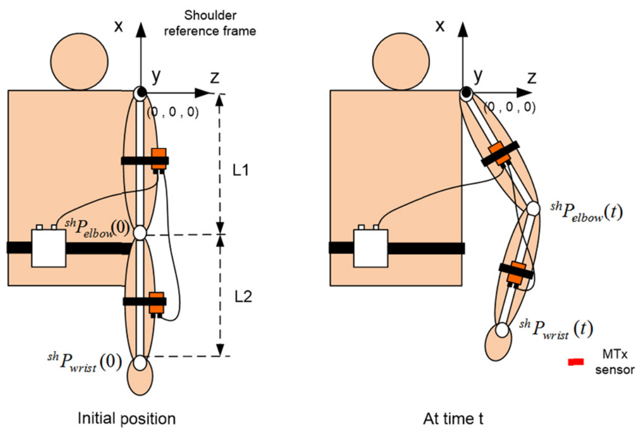


FIGURE 3. Two-sensor based kinematic model.

In this work, a two sensor kinematic model (Fig. 3) has been used to track upper limb motion. A shoulder reference frame that utilizes the shoulder as the reference point (0, 0, 0). It is assumed that the shoulder is fixed during the measurement. The initial position of the elbow is $^{sh}P_{elbow}\,(0)$ relative to the reference point, and the initial position of the wrist is $^{sh}P_{wrist}(0)$ relative to the elbow are expressed as $^{sh}P_{elbow}(0) = (-L1, 0, 0)^{T}$ and $^{sh}P_{wrist}(0) = (-L2, 0, 0)^{T}$ in the shoulder reference frame. Here, the lengths of the upper arm L1, forearm L2 have been measured in order to estimate the initial position of the elbow and wrist, which are also function as constraints in the upper limb kinematic model. The subscripts shoulder, elbow, wrist and hand are used for the shoulder, elbow, wrist and hand. The subscripts and superscripts sh, s and g are used to identify the shoulder, sensor and global reference frame. In (15), ${}^{g}_{s}R_{elbow}\,(t)$ refers to the rotation matrix which rotates the vector from the elbow sensor reference frame into the global reference frame and is obtained from the rotation matrix output of the sensor attached on the elbow as seen in the Fig.3. ${}^{sh}_{g}R_{elbow}\,(t)$ refers to the rotation matrix which rotates the vector from the elbow sensor in the global reference frame to the shoulder reference frame. The product of the above two matrices is ${}^{sh}_{s}R_{elbow}(t)$ is the rotation matrix which rotates the vector from the elbow sensor reference frame to the shoulder reference frame. Similarly the rotation matrix which rotates the vector from the sensor reference frame to shoulder reference frame of the wrist is ${}^{sh}_{s}R_{wrist}(t)$.

$$\begin{cases} {}^{sh}_{s}R_{elbow}(t) = {}^{sh}_{g}R_{elbow}(t) \cdot {}^{g}_{s}R_{elbow}(t) \\ {}^{sh}_{s}R_{wrist}(t) = {}^{sh}_{g}R_{wrist}(t) \cdot {}^{g}_{s}R_{wrist}(t) \end{cases} \tag{15}$$

When the subject's arm starts to move, the orientation output of the sensors will change and the position will change accordingly. As in (16), position outputs of elbow and wrist in the shoulder reference frame are ${}^{sh}P_{elbow}(t)$ and ${}^{sh}P_{wrist}(t)$ respectively. The elbow position ${}^{sh}P_{elbow}(t)$, for example, is calculated by multiplying the elbow rotation matrix ${}^{sh}_{s}R_{elbow}(t)$ ·(rotates the vector from the sensor reference frame to the shoulder reference frame) and the initial elbow position in the shoulder reference frame ${}^{sh}P_{elbow}(0)$, Similarly, the position of the wrist ${}^{sh}P_{wrist}(t)$ is calculated according to (16).

$$\begin{bmatrix} {}^{sh}P_{elbow}(t) \\ {}^{sh}P_{wrist}(t) \end{bmatrix} = \begin{bmatrix} {}^{sh}_{s}R_{elbow}(t) \cdot {}^{sh}R_{elbow}(0) \\ {}^{sh}_{s}R_{wrist}(t) \cdot {}^{sh}R_{wrist}(0) + {}^{sh}P_{elbow}(t) \end{bmatrix} \tag{16}$$

IV. EXPERIMENTAL WORK

A. LOW COST INERTIAL SENSOR CALIBRATION - SONY MOVE

Following the initial assessment of available devices, the experimental work focused on the Sony Move device that incorporates an IMU with 9DOF. Note that a similar approach can be applied on the use of smartphones with similar capabilities (See section IV.C.3).

1) STATIC CALIBRATION

There are three error sources which need to be taken into account. The sensor offset, sensor scale factor and relative orientation of the three sensors within the sensor packaging. It is assumed that the errors due to sensor orientation within the packaging are not significant compared to the sensor offsets and scaling factors.

a: ACCELEROMETER SCALE FACTOR AND OFFSET

In order to calculate the accelerometer offsets and scale factors, the gravitational acceleration (1g) is used as the reference input for the x, y and z axes when the sensor is static. Therefore the inertial sensor has to be tested in six positions with each of the three axes in line with the gravity direction respectively. Alignment is assumed to have been achieved when the output in the axis under calibration is maximized. The output is calibrated using (17).

$$y = scalefactor * x + offset(x = \frac{ADC}{2^{12}} * range_{acc}) \tag{17}$$

where y is the ideal gravitational acceleration, x is the sensor's output which is computed from sensor's 12-bit ADC output and $range_{acc}$ is the full scale of the accelerometer. The accelerometer scale factor and offset is obtained from (18) and (19) below.

$$scalefactor = \frac{2}{x_{max} - x_{min}} \cdot g \tag{18}$$

$$offset = \frac{x_{min} - x_{max}}{x_{max} + x_{min}} \cdot g \tag{19}$$

where x_{min} and x_{max} are the outputs from the accelerometers when the corresponding accelerometer axis is pointing in the direction of g and -g respectively. Hence the scale factors and offsets for the accelerometer x, y and z axes can be obtained.

b: GYROSCOPE OFFSET

The calibration process for the gyroscope differs from that of the accelerometer. The offset and scale factor are calculated through static and dynamic calibration respectively. The gyroscope offsets (on three axes) are computed from the static calibration by averaging the gyroscope outputs on all three axes (ω_x, ω_{-x}, ω_y, ω_{-y}, ω_z, ω_{-z}) with the zero-input by using (20).

$$\begin{cases} offset_{\omega_x} = \dfrac{\omega_x + \omega_{-x}}{2} \\ offset_{\omega_y} = \dfrac{\omega_y + \omega_{-y}}{2} \\ offset_{\omega_z} = \dfrac{\omega_z + \omega_{-z}}{2} \end{cases} \tag{20}$$

where (ω_x, ω_{-x}, ω_y, ω_{-y}, ω_z, ω_{-z}) are the averaged outputs from the corresponding gyroscope axis during the six static orientations of the calibration process for the accelerometer.

c: MAGNETOMETER CALIBRATION

The raw output from the Sony Move magnetometers (b_x, b_y, b_z) have arbitrary units which need to be calibrated (m_x, m_y, m_z) using the Earth's magnetic field by using (21), where $b_{||}$ and $b_{\perp}$ represent the horizontal magnetic and vertical magnetic fields at the location where the calibration procedure is implemented.

$$\begin{cases} m_x = \dfrac{b_x}{\sqrt{b_{||}^2 + b_{\perp}^2}} = \dfrac{b_x}{\sqrt{b_x^2 + b_y^2 + b_z^2}} \\ m_y = \dfrac{b_y}{\sqrt{b_{||}^2 + b_{\perp}^2}} = \dfrac{b_y}{\sqrt{b_x^2 + b_y^2 + b_z^2}} \\ m_z = \dfrac{b_z}{\sqrt{b_{||}^2 + b_{\perp}^2}} = \dfrac{b_z}{\sqrt{b_x^2 + b_y^2 + b_z^2}} \end{cases} \tag{21}$$

The earth's magnetic field (m) is composed of a horizontal magnetic field (mH) and vertical magnetic field (mV). These values can be calculated using the inclination angle I of the field as shown in (22) and the known value of the magnetic field at the longitude and latitude for the geographical location of the calibration. The inclination angle I is obtained from

TABLE 1. Accuracy of Euler angle measurement by the Xsens MTx, Sony Move and Nintendo Wii.

Accuracy(°)	MTx 1	MTx 2	MTx 3	MTx 4	MTx Average	Move 1	Move 2	Move Average	Wii 1	Wii 2	Wii Average
Roll	0.20	0.30	0.15	0.26	0.23	0.66	0.60	0.63	1.25	1.93	1.59
Pitch	0.21	0.27	0.21	0.22	0.23	1.09	0.84	1.19	1.24	1.52	1.38
Yaw	0.60	0.56	0.18	0.50	0.46	2.14	2.55	2.35	-	-	-

the magnetic field calculators for the geographical location of the calibration [30].

$$\begin{cases} m = \sqrt{m_H^2 + m_V^2} \\ m_H = cos(I) * m \\ m_V = sin(I) * m \end{cases} \tag{22}$$

As with the accelerometer calibration, estimates of the magnetometer scale factors and offsets are obtained by using (23) and (24) below.

$$scalefactor = \frac{2}{m_{max} - m_{min}} \cdot m_H \tag{23}$$

$$offset = \frac{m_{min} - m_{max}}{m_{max} + m_{min}} \cdot m_H \tag{24}$$

where m_{min} and m_{max} are the outputs from the magnetometers when the corresponding magnetometer axis points in the direction of magnetic north and south respectively. Through the above two equations, the magnetometer scale factors and offsets for the x, y and z axes are obtained.

2) DYNAMIC CALIBRATION - THE GYROSCOPE

In order to estimate the gyroscope scale factor, a known angular velocity is needed. In this case a high quality turntable, the Quartz Direct-Drive Turntable DJ-2500SQ which has two selectable synchronous motor speeds: 33.3 and 45 revolutions per minute (rpm) (3.487 rad/s and 4.712 rad/s), is used. In order to validate the turntable speeds the MTx is assumed to be calibrated and to be a reliable reference.

Five tests were carried out at both turntable speeds in order to validate the accuracy and stability of the turntable. The mean of MTx gyro output is 3.488±0.012 rad/s while the turntable is turning at a 33.3 rpm (3.487 rad/s) and 4.716±0.014 rad/s for a 45 rpm (4.712 rad/s) rotation. Therefore the turntable rotation speed is within 0.1% of the set value. This indicates that the turntable has adequate accuracy and can be used for calibrating the Sony Move or the gyros in any other inertial sensor.

The gyro scale factor is calculated using (25) below.

$$scalefactor_\omega = \frac{\omega_{output} - offset_\omega}{\omega_{ideal}} \tag{25}$$

where $scalefactor_\omega$ is the scale factor of the gyroscope, ω_{ideal} is the angular velocity of the turntable, ω_{output} is the output from the gyroscope and the gyroscope offset $offset_\omega$ is the value obtained through the static calibration of section IV.A.1.

3) SENSOR DATA SYNCHRONIZATION

In order to compare the performance of the Xsens MTx and Sony Move systems, data synchronization is required. Within each of the sensing system, there is no need to implement the synchronization. The participants are asked to stay stationary before each of the tests. The start of the motion will be deemed as the trigger for data synchronization for both systems. In (26), the short time energy E_i is used for detection of the start of the motion where i is the discrete time. When E_i reaches the threshold, the data synchronization starts.

$$E_i = \sum_{i=1}^{N} \sqrt{\omega_x(i)^2 + \omega_y(i)^2 + \omega_z(i)^2} \tag{26}$$

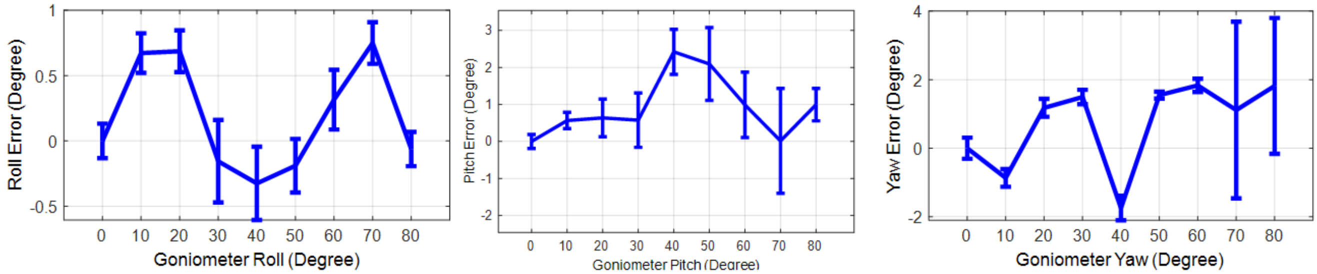
B. ACCURACY OF THE LOW COST INERTIAL SENSORS

In this section, the static accuracy of orientation estimation is evaluated when the sensor is put in known orientation or positions. In order to check the static orientation accuracy, the MTx sensors are attached to a goniometer and the orientation then changed (from 0 degree to 80 degree). The accuracy of the goniometer can be 0.25 degree in measuring static orientation whereas that of the MTx is 0.5 degree. The measurements were repeated for four MTx inertial sensors of the 9 unique orientation ranges from 0 degree to 80 degree. Each measurement lasts for 30 seconds, which is a measurement of 1500 samples. The mean values and standard deviations of each measurement episode are presented in Fig. 4.

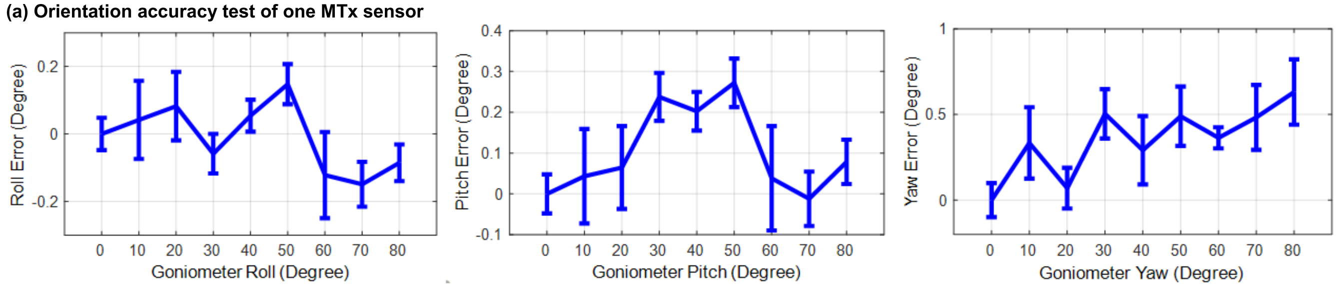
Unlike the MTx sensors, the orientation output cannot be directly obtained from the low cost sensors. But the static 3D orientation accuracy of the low cost inertial sensors can be calculated using the accelerometer, gyroscope and magnetometer outputs for the Sony Move. And 2D orientation of the Nintendo Wiimote can be calculated using accelerometer only. The 3D orientation calculation algorithm has been presented in section III.B.1. The accuracy of the Euler angle (Roll, Pitch and Yaw) output for the four MTx, two Sony Move and Euler angle (Roll and Pitch) for two Wiimote are shown in Table 1.

The outcome of the Roll, Pitch and Yaw accuracy measurements for the Sony Move are Roll 0.63°, Pitch 1.19° and Yaw 2.35°, compared with the manufactures data for the MTx of Roll and Pitch 0.50° and Yaw 1.00°.

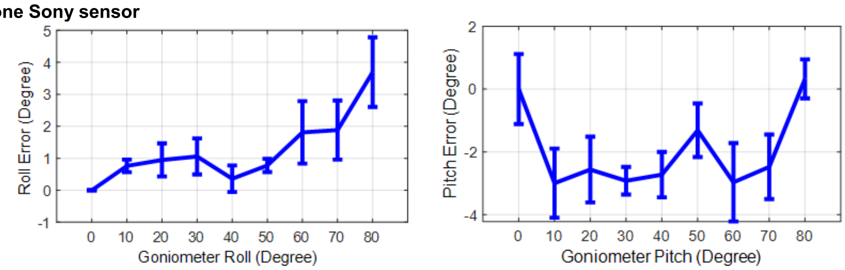
The Sony Move performance indicates that it might be a possible choice to replace the Xsens MTx for some upper limb motion monitoring applications. The reason for the lower accuracy in the Yaw measurement requires further investigation. The accuracy of the gyro output under dynamic conditions was evaluated by placing the sensors



(a) Orientation accuracy test of one MTx sensor



(b) Orientation accuracy test of one Sony sensor



(c) Orientation accuracy test of one Wiimote sensor

FIGURE 4. Sensor orientation accuracy for Xsens MTx, Sony Move, Wiimote.

on to the turntable. The turntable was rotated at 45 rpm (4.712 rad/s) and the gyro data collected for 3 revolutions over approximately 4 seconds. The gyro results from the MTx, Sony Move, Wii and Smartphone are: the Nintendo Wii (4.71±0.03 rad/s), Sony Move (4.71±0.01 rad/s) and Smartphone (4.71±0.01 rad/s) estimate the angular velocity to within 0.2%. The cause of the noise in the Wii data which occurs on every revolution of the turntable is to be investigated.

In order to check the performance of the complementary and Kalman filters and the kinematic models, basic tests were carried out to measure changes in joint angle and segment trajectory. The first test is measurement of a 2D range of movement and sensor trajectory in a simple two-segment kinematic model.

C. MEASUREMENT OF RANGE OF MOVEMENT

1) EVALUATION OF THE COMPLEMENTARY AND KALMAN FILTER - ORIENTATION

Fig. 5 (a) shows a 2D two-segment upper limb set-up using a goniometer with the MTx and the Sony Move to simultaneously measure the Roll angle and trajectory of the end of the goniometer arm. One arm of the goniometer is fixed and the other, to which the sensors are fixed, is rotated through 60°.

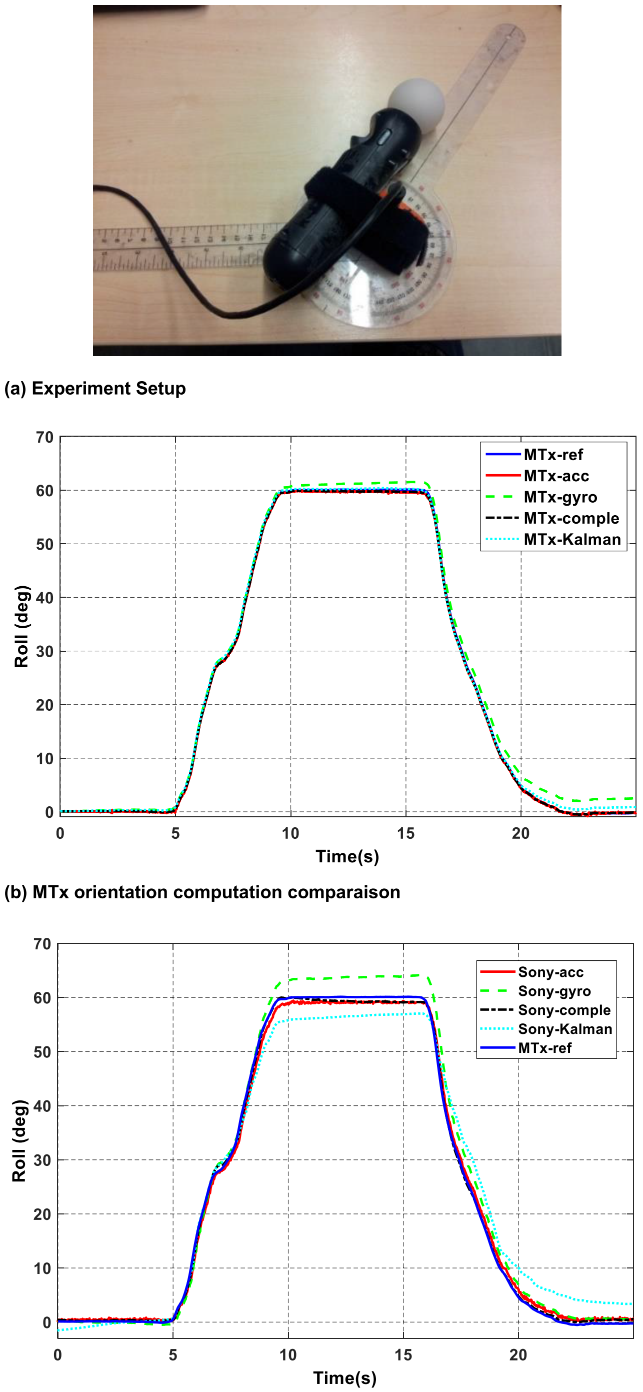
The changes in orientation were calculated by fusing the accelerometer, magnetometer and gyroscope outputs, and then applying a complementary filter or a Kalman filter. Estimates of the change in roll angle were also made using accelerometer & magnetometer only and gyro only data. The estimates of roll angle for the MTx and Sony Move are presented in the plots Fig. 5 (b) and (c) respectively.

Using the internal Xsens Kalman Filter algorithms, MTx-ref, as the reference, then errors in the estimates of the change in orientation for the MTx (see Fig. 5(b)) using the four algorithms are:

- Accelerometer and magnetometer output - MTx-acc - error 0.30°
- Gyro output alone - MTx-gyro - error 1.60°
- All sensors and complementary filter - MTx-comple - error 0.20°
- All sensors and Kalman filter - MTx-Kalman - 0.60°

The plots in Fig. 5 (c) present the roll output for the MTx-ref and the Sony Move. The estimated errors for the Sony Move and the four algorithms are:

- Accelerometer and magnetometer output - Sony-acc - error 1.6°
- Gyro output alone - Sony-gyro - error 4.1°
- All sensors and complementary filter - Sony-comple - error 0.5°
- All sensors and Kalman Filter - Sony-Kalman - error 3.1°



(a) Experiment Setup

(b) MTx orientation computation comparaison

(c) Sony Move orientation computation comparison

FIGURE 5. Comparison of the Sony Move with the MTx: Roll test for using four different algorithms.

The plots in Fig. 5 (b) and 5 (c) and the errors indicate that the complementary algorithm developed in this research provides the best estimate of the roll angle for the MTx (0.2°) and for the Sony Move (0.5°). As expected, the estimates using the gyro output alone have greater errors - thought to be caused by the inherent drifts in the gyro sensors.

However this test only measures 2D rotation. In order to evaluate the system under the more challenging and realistic conditions when the movement is in three dimensions and/or linear motion is present upper-limb motion will be monitored with the MTx and the Sony Move sensors.

TABLE 2. Details of the patients.

Patient No.	1	2	3	4
Gender	Male	Male	Female	Male
Age	72	76	75	69
Brain lesion	Right MCA infarct (parietal lobe)	Right thalamic infarction	Right MCA infarction	Right MCA infarction
Stroke duration	2 yrs	4 yrs	4 yrs	2 yrs
Muscle Injected	Bicep, FDP, FDS	Pectoralis Major, FDP, FDS, FCR, FCU	FDP, FDS, Bicep and Brachiora-dialis	FDP, FDS and Bicep and Brachi-oradialis

Acronym: FDP: Flexor Digitorum Profundus, FDS; Flexor Digitorum Superficialis, FCU: Flexor Carpi Ulnaris, FCR: Flexor Carpi Radialis; MCA: Middle cerebral artery

2) EVALUATION OF THE SENSOR SYSTEM USING THE RANGE OF MOTION TEST ON A HEALTHY VOLUNTEER AND PATIENTS

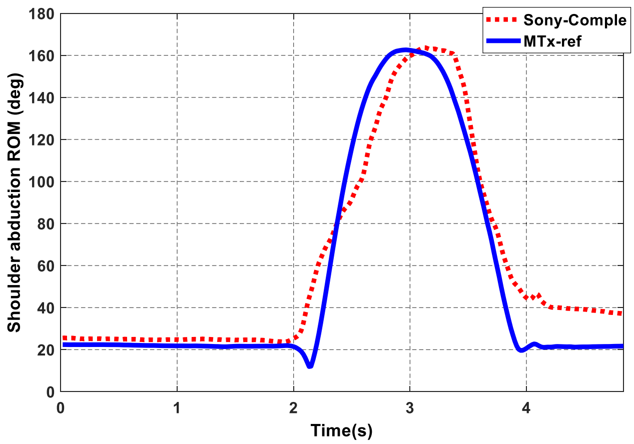
Four patients undergoing Botulinum Toxin treatment were recruited (See TABLE 2) to investigate the effect of that treatment on upper limb spasticity. Written informed consent was obtained from each subject before enrolment and participation in this study. Ethics permissions were obtained from the UK NHS National Research Ethics Committee [IRAS 25835] and the Hospital Institutional Review Board (IRB).

The measurement of joint range of movement (ROM) is one important test for patients who are undergoing rehabilitation. It is used to help assess recovery of the patient's ability to perform daily activities [31]. The traditional method to measure ROM is to use a goniometer, however this can only measure in 2D and is basically a static measurement. Therefore, this instrument does not provide any information about the way in which the movement is performed or any dynamic data. However the inertial measurement system will not restrict movement to 2D and is also able to provide the clinician with information about dynamic limb segment movement.

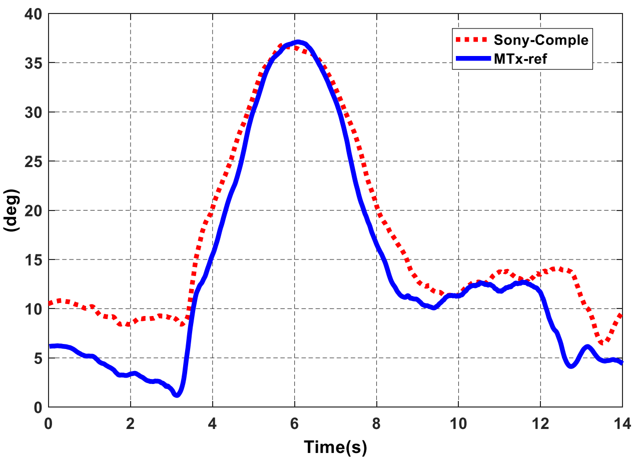
A typical set-up to track upper limb joint range motion is shown in Fig. 6 (a). In this case the trunk reference frame and a two-segment biomechanical model is to be used. It should also be noted that the alignment of the sensors is critical to the accuracy in the upper limb orientation measurement. In this study, the sensors (x-axis) on the upper arm and lower arm should be in parallel with the skeleton axis of the upper limb [5]. Results for a shoulder abduction test from the MTx and Sony Move for a healthy volunteer are shown in Fig. 6 (b) and those for a patient are shown in Fig. 6 (c). In the shoulder abduction test, the subject is asked to pull the upper limb away from and towards the midline of the body in the frontal plane.

The synchronization of the two measurement systems was achieved by the known initial conditions of the experiments.

(a) Experiment Setup



(b) Healthy volunteer



(c) Patient

FIGURE 6. Measurement of range of motion with MTx and Sony Move sensors.

The subjects were asked to stay stationary with their arms aligning on the side of their body before the start of the test and keep stationary after the experiment tasks completed.

The outcome for the normal volunteer shows that the ROM for the MTx is 140° and for the Sony is 138°, with some drift in the Sony measurement at the end of the maneuver, which is possibly caused by movement of the Sony on the patient, indicating an attachment issue. However, it can also be seen that the dynamic information indicates a relatively smooth movement whilst performing the test. In this case the healthy volunteer has good control of the upper limb motion and examination of the movement in the other axes shows that the movement is contained within a 2D plane.

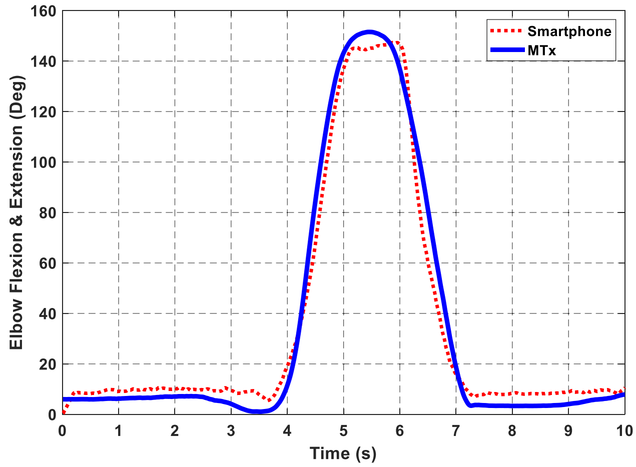


FIGURE 7. Elbow Extension Orientation tracking with MTx and Smartphone.

However, it can be seen that with the neurological patient as well as having a greatly restricted ROM of approximately 30°, the time dependence and movement morphology is significantly different from that of the normal volunteer. This indicates that the patient is having difficulties performing the manoeuvre. The difference in response of the two systems for a given subject is thought to be caused by misalignment and movement of the Move. However, these differences are not thought to be clinically significant. The clinical value of this dynamic information requires further investigation.

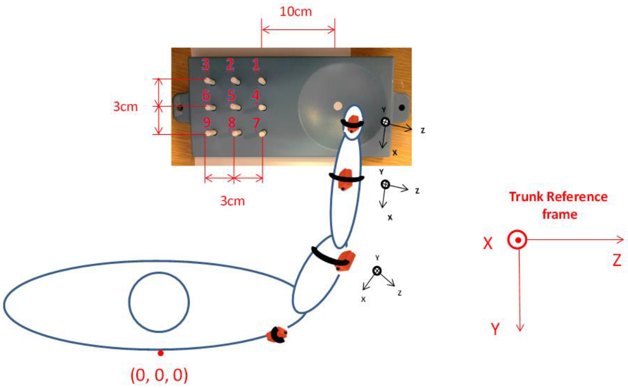
3) PRELIMINARY EVALUATION OF ORIENTATION TRACKING WITH A SMARTPHONE

Because of the availability and popularity of smartphones - and now fitness/activity trackers and smart watches - a test was performed using a smartphone to evaluate the suitability of this emerging technology for this application. The smartphone was strapped to the lower arm of a healthy volunteer and the basic range of motion (elbow extension) test of Section IV.C.1 carried out. Because only a single smartphone is used, the volunteer was asked to keep their upper arm stationary. The simultaneous measurements taken with one MTx and the Smartphone (Samsung Galaxy II) are shown in Fig. 7. The outcome is that the smartphone can measure to within 5° over a 150° of ROM.

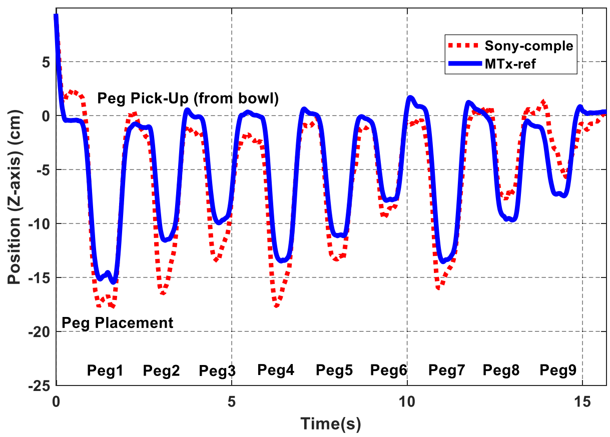
D. MEASUREMENT OF LIMB SEGMENT POSITION

1) MEASUREMENT FOR HEALTHY VOLUNTEER

In this evaluation, two Sony Moves and a two-segment kinematic model is used, with segment movement presented in the trunk reference frame. Fig. 8 (a) shows a typical set up with a healthy volunteer carrying out a standard assessment using the Nine-hole peg test [32]. In this test the MTx sensors are also attached to the volunteer as shown in Fig. 8 (a). In this test the therapist measures the time taken to complete the test and observes limb segment movements, both of which can be measured by the inertial system.



(a) Nine-Hole Peg Test set-up



(b) Hand Position tracking using two Sony Moves & two MTx sensors in the Z axis

FIGURE 8. **3D Position tracking for Nine-Hole peg test.**

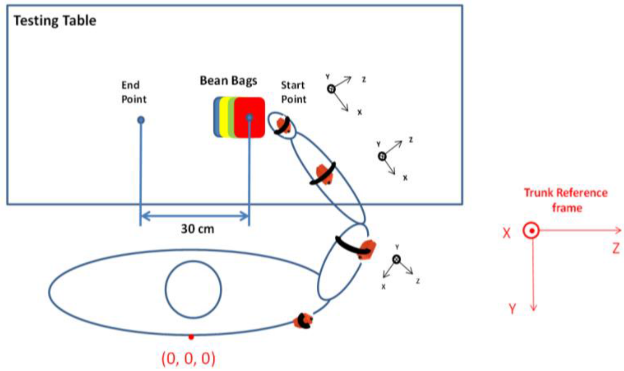
The estimated 3D orientation of the two controllers in the trunk reference frame and the kinematic model are used to calculate limb segment 3D position. The movement of interest is in the z-axis of the trunk reference frame as shown in Fig. 8 (b). The wrist position is estimated using the Sony Move Complementary filtered model and is compared with that of the MTx system. It is assumed that the shoulder and trunk are kept stationary so that there is a fixed correspondence between the trunk reference frame and the nine-hole peg board.

The distance between the peg holes is 3 cm. In the z axis representation it would be expected that the spacing between the pegs for the series 1-3, 4-6 & 7-9 should be 3 cm. The distances between the pegs estimated from the plot are shown in Table 3.

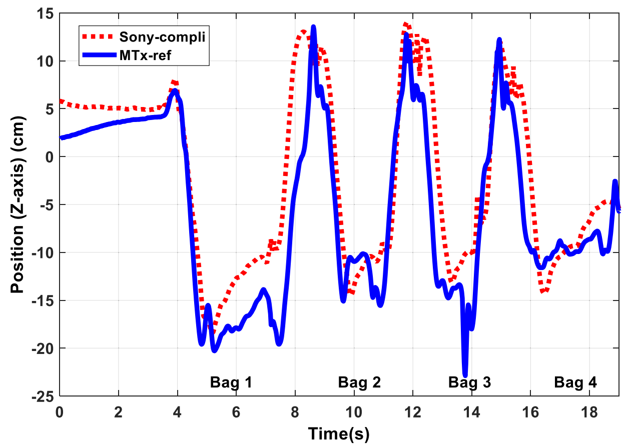
2) MEASUREMENT FOR PATIENT UNDERGOING NEUROLOGICAL REHABILITATION

Another common assessment during rehabilitation is the bean bag test [33]. The setup is shown in Fig. 9 (a). In this test the patient has to move bean bags from one position to another. The therapist will observe how this is accomplished and may also time how long the test takes to perform. The test setup is given in Fig. 9 (b) and position tracking result for one test is presented in Fig. 9 (c).

(a) System setup on patient



(b) Bean bag test



(c) Patient wrist position tracking - Bean bag test (MTx two-sensor modelling)

FIGURE 9. **Bean bag Test - Hand/Wrist tracking in the z-axis.**

TABLE 3. **Estimated distances between pegs.**

Sensor/Peg	1-2	2-3	4-5	5-6	7-8	8-9
Xsens MTx (cm)	3	2	2	3	3	2
Sony Move (cm)	1	3	3	3	6	1

Again this is a two sensor and two segment kinematic model. It is assumed that the relationship between the trunk reference frame and the surface of the table does not change. It is that also assumed that there is no movement of the patient's shoulder or trunk during the test.

The relative movement of the wrist/hand in the z axis from Fig. 9 (c) for each bag was measured to be approximately 27 cm for the MTx system and 26 cm for the Sony system. The estimates of the distances moved for each bag transfer are within 2 cm (Table 4). The difference in profiles between

TABLE 4. Estimated distances between start and end points (Bag Movement- expected ~30cm).

Sensor/Peg	1	2	3	4
Xsens MTx (cm)	27	27	27	27
Sony Move (cm)	26	25	27	25

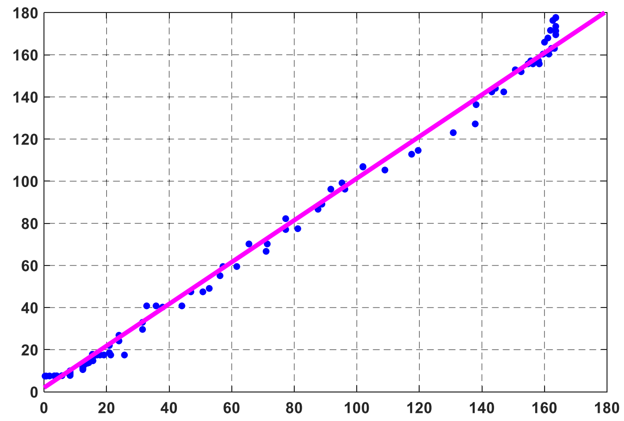


FIGURE 10. Inter-Trial pearson correlation plot.

the MTx and Sony Move measurements are thought to be due to alignment differences between these two different sensors and possible movement of the Sony sensors during the test. However, in this assessment the timing and the smoothness of each movement rather than the distances travelled are the key measures. Therefore a Sony two sensor system can still provide useful kinematic data for this particular test.

It should be noted that in this presentation only the movement in the z direction in the z-y plane is presented. The system can capture movement in the x and y axes as well. These are additional datasets that can offer further information about the way in which the participant is performing each test.

E. TEST AND RETEST RELIABILITY

To ensure that reliability was quantified for different joint angles, a healthy volunteer had been asked to perform all the tests as that of the patients. Fig. 10 shows the Inter-Trial Pearson Correlation for the orientation measurement of the healthy volunteers in Shoulder Abduction and Adduction test. Two orientation test results were compared after Dynamic Time Warping as the length of the measurements are different. The result for Pearson Correlation Coefficient after Dynamic Time Warping is 0.997 ($P<0.001$).

V. DISCUSSION

The feasibility of using low cost inertial sensing units to measure upper limb motion has been investigated. In this study the Nintendo Wii, Sony Move and a smartphone have been evaluated. A high-accuracy inertial sensing unit, Xsens MTx, is used as a reference. This study based solely on low cost IMU to measure upper limb motion as most of the previous studies were focused on using camera based solutions or integrating IMU with camera. Our solution makes the upper limb monitoring process simple and reliable without using a camera based system.

A. GYRO ACCURACY ANALYSIS

Comparisons of the raw gyro data among the different sensors are presented in Section IV.B. The accuracy of the gyros in the Sony Move and the smartphone is the same as that of the MTx and should be suitable for measuring the dynamic limb segment orientation.

B. ORIENTATION ESTIMATION ERROR ANALYSIS

As seen in Fig. 5, the increase in error compared to the MTx output is thought to be due to the lower quality sensors used, possible errors in estimating the sensor gains and offsets and misalignment of the sensors within the Sony Move. Further work is required to investigate whether a more accurate measurement of sensor gain and offsets that will help to further reduce these errors.

C. NINE-HOLE PEG TEST RESULTS WITH MTX ANDMOVE

As can be seen from Fig. 8 there is some baseline wander for the MTx model ($\pm$1cm) and increased baseline wander in the Sony Move model ($\pm$2cm) which partially masks the actual movement of the wrist. This drift is caused by the picking up of the pegs from different locations in the bowl and also errors introduced by the fact that the two-segment kinematic model assumes that there is a fixed relationship between the trunk and peg board reference frames. If there is any movement of the shoulder or trunk during the test then that assumption is no longer valid. Additionally it is assumed that there is no movement of the hand and fingers relative to the wrist. The increased errors for the Sony Move may originate from the calibration errors and movement of the Move on participant's arm during the test. This indicates the difficulty of securely attaching the Move to the participant. Nevertheless these results indicate that, with improvement in calibration and a more secure attachment, the Sony Move system compares favorably with that of the MTx and could provide a low cost replacement in a two segment model.

D. RANGE OF MOTION MEASUREMENT WITH SMARTPHONE

The range of motion measured with the smartphone and the MTx is within 5° over a 150° movement. This outcome indicates that a smartphone with a tri-axial accelerometer, magnetometer and gyro could also be used for the basic measurements of upper limb movement. The smartphone could provide additional advantages over the MTx because of its wireless or mobile communication functions.

E. LIMITATION OF THE LOW COST SYSTEM

Although the proposed sensing system provides enough accuracy, it is limited to the two sensor model dues to the bulky size of the Sony Move sensor. It is not viable to attach additional sensors on the hand and shoulder. The low cost sensor system can only track the wrist and elbow motion.

VI. CONCLUSION

The feasibility of using low cost inertial sensor systems such as the Sony Move, Wii Remote and the Samsung Galaxy II Smartphone, for upper limb movement monitoring has been investigated. 3D sensor orientation is estimated using data fusion techniques that implement Kalman and complementary filters. Furthermore a two-segment kinematic model was developed to estimate limb segment position tracking. For two-segment tracking the inertial sensor system must contain a 3-axis accelerometer, gyroscope and magnetometer. Performance has been compared with a high-accuracy measurement system using the Xsens MTx. The Sony Move can track position to within 0.5 cm over a 10 cm movement and orientation to within 1.5° for roll, pitch and within 2.5° for yaw. The MTx system can measure static angles with an error no greater than 0.5° (Roll & Pitch), 1° (Yaw) and within 0.1 cm for a change of position of 10 cm [5].

This accuracy in measurement is thought to be adequate for upper limb orientation and position tracking. Based on these results the Sony Move may be considered as an alternative to the MTx inertial sensors for biomechanical use where a two-sensor system is needed, and when there is no particular requirement for orientation accuracy better than a few degrees and when the subject is comfortable with the size of these gaming sensors. Similarly, preliminary measurements with the smartphone indicated that orientation could be measured to within 1 degree for Roll and Pitch and within 2° for Yaw. Because the measurement of 3D movement requires a sensor with a tri-axial accelerometer, gyro and magnetometer, the Wiimote, which does not contain a magnetometer, is only suitable for estimation of the roll and pitch orientation.

It is noted that the size of the Sony Move is relatively bulky compared with the Xsens MTx sensors. With the advancement of the sensing technologies, the smaller low cost wireless inertial sensors are becoming possible. This paper aims to provide a proof of concept for quantitative assessment of the upper limb movement using low cost inertial sensors in Neurorehabilitation and provide guidance on using low cost inertial sensors in the assessment of upper limb rehabilitation. More recently, smart watches and fitness trackers have emerged as wrist wearable inertial sensing units that can capture limb motion data [15], [16]. Fitness trackers with a real-time 9DOF Inertial Measurement Unit (IMU) may, therefore, prove to be an attractive replacement for the larger gaming sensors and smartphone as they are small and designed to be attached to the upper limbs. Therefore the overall outcome of this study is that low cost 9DOF inertial sensors, combined with a kinematic model, can measure limb segment orientation and position with acceptable accuracy for clinical applications.

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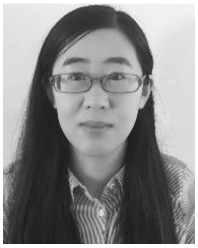

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